- 27 -

To further increase the accuracy of the comparison, each yearly vintage is divided into four quarterly portfolios, i.e. first, second, third and fourth quarters. All of the 1993 portfolios of the same quarterly age are summed and divided by the total number of all the loans with the same respective age. Referring again to Fig. 3, the present invention separately compares the 1993 and 1994 24 month old loans, then the 21 month old loans and so on. The actual mathematical calculations/analysis comparing loans originated in 1993 and 1994 and the manner of calculating bad rates is shown below in Tables I, II and III.

TABLE I

	Age (Months)	3	6	9
1993 Vintage	# of Loans (n)	n_3	n_6	n_9
	BAD rate (r)	r_3	r_6	r_9
	STD	$Sqrt(r_3*(1-r_3)/n_3)$	$Sqrt(r_6*(1-r_6)/n_6)$	$Sqrt(r_9*(1-r_9)/n_9)$
1994 Vintage	# of Loans (N)	N_3	N_6	N_9
	BAD rate (R)	R_3	R_6	R_9
	STD	$Sqrt(R_3*(1-R_3)/N_3)$	$Sqrt(R_6*(1-R_6)/N_6)$	$Sqrt(R_9*(1-R_9)/N_9)$
1994-1993	Difference (R-r)	R_3-r_3	R_6-r_6	R_9-r_9
	STD of (R-r)	$STD_3=Sqrt(r_3*(1-r_3)/n_3+R_3*(1-R_3)/N_3)$	$STD_6=Sqrt(r_6*(1-r_6)/n_6+R_6*(1-R_6)/N_6)$	$STD_9=Sqrt(r_9*(1-r_9)/n_9+R_9*(1-R_9)/N_9)$
	Upper Bound	$+1*STD_3$	$+1*STD_6$	$+1*STD_9$
	Lower Bound	$-1*STD_3$	$-1*STD_6$	$-1*STD_9$

TABLE II

		12	15	18
	Age (Months)	12	15	18
1993 Vintage	# of Loans (n)	n_{12}	n_{15}	n_{18}
	BAD rate (r)	r_{12}	r_{15}	r_{18}
	STD	$Sqrt(r_{12}*(1-r_{12})/n_{12})$	$Sqrt(r_{15}*(1-r_{15})/n_{15})$	$Sqrt(r_{18}*(1-r_{18})/n_{18})$
1994 Vintage	# of Loans (N)	N_{12}	N_{15}	N_{18}
	BAD rate (R)	R_{12}	R_{15}	R_{18}
	STD	$Sqrt(R_{12}*(1-R_{12})/N_{12})$	$Sqrt(R_{15}*(1-R_{15})/N_{15})$	$Sqrt(R_{18}*(1-R_{18})/N_{18})$
1994-1993	Difference (R-r)	$R_{12}-r_{12}$	$R_{15}-r_{15}$	$R_{18}-r_{18}$
	STD of (R-r)	$STD_{12}=Sqrt(r_{12}*(1-r_{12})/n_{12}+R_{12}*(1-R_{12})/N_{12})$	$STD_{15}=Sqrt(r_{15}*(1-r_{15})/n_{15}+R_{15}*(1-R_{15})/N_{15})$	$STD_{18}=Sqrt(r_{18}*(1-r_{18})/n_{18}+R_{18}*(1-R_{18})/N_{18})$
	Upper Bound	$+1*STD_{12}$	$+1*STD_{15}$	$+1*STD_{18}$
	Lower Bound	$-1*STD_{12}$	$-1*STD_{15}$	$-1*STD_{18}$

TABLE III

		21	24	27
	Age (Months)	21	24	27
1993 Vintage	# of Loans (n)	n_{21}	n_{24}	n_{27}
	BAD rate (r)	r_{21}	r_{24}	r_{27}
	STD	$Sqrt(r_{21}*(1-r_{21})/n_{21})$	$Sqrt(r_{24}*(1-r_{24})/n_{24})$	$Sqrt(r_{27}*(1-r_{27})/n_{27})$
1994 Vintage	# of Loans (N)	N_{21}	N_{24}	N_{27}
	BAD rate (R)	R_{21}	R_{24}	R_{27}
	STD	$Sqrt(R_{21}*(1-R_{21})/N_{21})$	$Sqrt(R_{24}*(1-R_{24})/N_{24})$	$Sqrt(R_{27}*(1-R_{27})/N_{27})$
1994-1993	Difference (R-r)	$R_{21}-r_{21}$	$R_{24}-r_{24}$	$R_{27}-r_{27}$
	STD of (R-r)	$STD_{21}=Sqrt(r_{21}*(1-r_{21})/n_{21}+R_{21}*(1-R_{21})/N_{21})$	$STD_{24}=Sqrt(r_{24}*(1-r_{24})/n_{24}+R_{24}*(1-R_{24})/N_{24})$	$STD_{27}=Sqrt(r_{27}*(1-r_{27})/n_{27}+R_{27}*(1-R_{27})/N_{27})$
	Upper Bound	$+1*STD_{21}$	$+1*STD_{24}$	$+1*STD_{27}$
	Lower Bound	$-1*STD_{21}$	$-1*STD_{24}$	$-1*STD_{27}$

Table I contains the calculations and comparisons for 1993 and 1994 loans which have vintage ages of 3, 6 and 9 months; Table II does the same for loans aged 12, 15 and 18 months; and Table III does so for loans that are 21, 24 and 27 months. The first line in Tables I-III sets forth the total number (n_3, n_6, etc.) of loans of the given vintage. The second line in the

- 29 -

Tables sets forth the bad rates (r_3, r_6, etc.) for each

vintage age. The third line calculates the standard

deviation (STD) of the bad rate, using the indicated

equations. The first three lines of Table I supply the

5   relevant information and calculations for the 3, 6 and 9

month old 1993 vintage. The next three lines of Table I

supply the same information for the 1994 vintage. The

bottom four lines of Table I calculate the differences

and compare the results for 1993 and 1994 vintage years.

10   The last two lines calculate upper and lower bounds for

the standard of deviation. The two bounds are plus one

and minus one standard deviation, but management can set

this based on their tolerance for default risk. These

calculations constitute the Crus Classes method 30 of the

15   invention whose effect can be appreciated from reviewing

the analysis results plotted in Fig. 4.

        That is the values calculated in Tables I, II

and III above for the differences between vintages 1994

and 1993 are plotted in the graph of Fig. 4 relative to a

20   zero percentage base 71. The curve 70 represents the

magnitude of the difference in the "bad" rates of loans

of the same age. The value of the curve 70 equals r_3-R_3;

r_6-R_6; etc. shown in Tables I-III. One would be tempted

to assume that the 1994 vintage performs better than the

25   1993 anytime the value of the curve 70 goes over zero

- 30 -

percent and vise versa. However, such a mode of
analyzing the data would be subject to reaching wrong
conclusions due to statistical variations. To overcome
this drawback, it is more significant to ask whether a
5   vintage that appears to perform better does so in fact or
whether it merely reflects a temporary phenomenon. To
answer the question, the invention uses a hypothesis
testing technique which allows the analyst to set a
confidence interval which is adjustable to allow for
10   different corporate risk tolerance levels. Thus, the
confidence interval can be equated to the amount of risk
tolerance management will accept in originating,
purchasing, retaining or servicing loan portfolios.
These confidence intervals can also be used in product
15   profitability and capital allocations. Management can
then rank the vintages by product, program, age and size.
To this end, the Tables presented above also calculate
the standard deviation of the difference in performance
and sets upper bounds and lower bound of +1 and -1
20   standard deviations for each quarterly vintage. These
upper and lower limits which appear in the last two lines
of Tables I, II, III are plotted in the form of curves 66
and 68 in Fig. 4. The area between the curves 66 and 68
is an area of uncertainty.

- 31 -

With this in mind, since the invention
superimposes the curve 70 over the area of uncertainty,
one can state with greater certainty which vintage
performs better only in the areas outside the area of
5   uncertainty. Thus, the graph of Fig. 4 shows that the
1994 loan vintages are "better" than corresponding 1993
loan vintages for loans that are 6, 21 and 24 months old.
On the other hand, the 1993 vintage appears to be better
for loans that are 27 and 30 months old. During other
10   months, the result is too close to conclude with the
chosen degree of certainty which vintage is better. The
chart of Fig. 4 underscores the fallacy of the prior art
in referring to yearly vintages as better or worse. One
must be more specific as to time and other criteria,
15   since relative performance changes dynamically with time.

While the invention has been described above in
relation to the consideration of vintages in yearly
quarterly units, note that in the loan industry exogenous
factors such as changes in economy, unemployment and
20   inflation are time varying factors that vary greatly over
an annual interval and therefore the system of the
invention permits analysis based on the choice of any
interval unit. The important thing to realize is that in
general, a new mortgage loan is more sensitive to small
25   changes in delinquency performance than an older

- 32 -

mortgage. This is shown by widening of the confidence
interval bands over time. So in essence, the application
of the above described Crus Classes method corrects for
this fact.

5   The invention also takes and adjusts the
vintage rating based on quality comparisons for different
volatilities of default. In essence, using the system
lets the user to set policies with respect to
volatilities of default which is another form of risk
10   management. This is new to the industry.

The confidence level in the assessment of the
difference in quality between groups of loans depends to
a certain degree on the sample size of the loans. For
small groups of loans, one will always be less certain of
15   their performance. The real question is how much less
certain. This is answered with the Crus Classes method.
The Crus Classes method also automatically adjusts the
comparison for different sample sizes of loans in each
node or product. This is evident in the calculations in
20   the previously presented tables which always take into
account the number of loans. An actual calculation that
has been carried out to evolve the vintage comparison
graph of Fig. 4 in accordance with Tables I, II and III
is presented in Fig. 4A.

- 33 -

As described above, the Crus Classes method 34
delivers a comparison of two loan vintages either in the
form of a graph or tabulated data which permits one to
get a sense of which vintages are performing better.
This information can then be used in making manual or
automatic, computer generated yes/no decisions whether to
originate, purchase, or to maintain and sell various
vintages of loan products or servicing rights as needed
at the decisional blocks 13, 24 and 32 of Fig. 1.

The basic premise of the Crus Classes analysis
is that the future performance of these loan vintages
will match the past pattern. This may not necessarily be
true. To this end, the early warning system (EWS) 32 of
the present invention further enhances the loan analysis
process by incorporating an application of behavioral
scoring that has been specifically designed to be used on
closed end loans with longer maturities such as
mortgages. The EWS 32 is able to statistically predict
the probability that a group of loans will experience
credit performance problems during a future preselected
time period, without waiting for that loan to season. In
the case of mortgages, the time to season is typically
three to seven years. The EWS 34 is intended to provide
management with automated analytical tools which allow

- 34 -

making decisions well in advance of the aforementioned
three to seven "seasoning" period.

By utilizing the EWS, a mortgage originator can
perform portfolio analysis and ascertain which product
5   type, program, type of underwriting, property type, type
of customer, origination channel, etc. is at risk,
without waiting for the mortgages to actually mature and
enter default. The only constraint is the amount of data
attributes that the mortgage loan originator keeps on any
10   customer over time, which for the purposes of the present
invention may be two years. The mortgage originator can
then dynamically adjust the flow of origination by
altering any credit criteria derived from a particular
attribute.

15   The EWS 34 constitutes the dynamic component of
the underwriting concept of the present invention. With
this concept, the decision maker can estimate
improvements in credit quality for each specific type or
amount of change in a criteria, i.e. he or she can
20   calculate the marginal contribution of any attribute on
record.

More specifically, the forward looking feature
of the EWS component of the invention attempts to
forecast the likelihood the borrowers will enter a 90+
25   days past due delinquency on their mortgages. This

- 35 -

condition -- the occurrence of a 90-day past due
delinquency -- is defined as a "bad" condition relative
to any loan. The EWS calculates the probabilities of bad
conditions occurring by combining loan information with
5   the credit bureau's current behavioral score for the
given borrower. In other words, the EWS combines the
borrower's current mortgage status (default status and
age) with a forecast that is based on the borrower's
performance on other obligations and uses this
10   information to forecast the bad condition. The EWS
system makes three major assumptions:

- The future performance pattern of defaults
  will be the same as in the past;
- The future performance depends upon the
15   current loan characteristics and is
  dependent on past performance only through
  the credit bureau scores. Therefore, the
  EWS also carries all the assumption of the
  credit bureau's score that was used; and
20   - The EWS employs a logistic regression model
  to accurately and sufficiently predict
  default behavior.

The aforementioned "bad" condition is a
discrete (yes or no) event that occurs when and if an
25   individual loan is at least once three payments past due

- 36 -

at any point during a forward looking preset time period,
for example, two years. Bad loans are assigned the value
"1" and good loans the value "0". How many times the
loan enters "bad" is not considered in the EWS. A good
5   loan is never three payments past due over the
aforementioned two year time frame and therefore is
assigned a loan of a value "0". Preferably, in order to
provide reliable information using the EWS system, the
underlying portfolio should have at least 100,000 loans
10   and the loans should consist of different distributions
of ages, types, locations, etc. In an embodiment of the
invention which has been reduced to practice the number
of loans in the portfolio exceeded one million.

The EWS probability of loans entering the bad
15   condition is developed or calculated on the basis of
looking backward in time through a development period
which may similarly constitute a two-year time period.
The EWS formula considers the age of the loan at the
beginning of development period; the credit bureau score
20   for the loan at the beginning of the development period;
the delinquency status at the beginning of the
development period; and the type of product, for example,
whether a government or conventional or adjustable rate
mortgage, etc.

- 37 -

The following logistic model has been applied to the underlying portfolio (government and conventional loans being considered separately). In the formula shown below, P is the probability of a loan becoming bad at any time in the coming two years:

$$Log(P/(1-P)) = A + (B_1*AGE) + B_2*C0 + B3*D_1 + B4*D_2 + B_5*SCORE + B_6*NO\ SCORE).$$

In the equation, AGE is defined in categories of quarters from 1-40. Therefore B_1 and AGE are 40 dimension row and column vectors respectively. SCORE is the mortgage score from a credit bureau rating company such as the well known Equifax rating bureau, at the beginning of the two-year time period, i.e. August 1994. Note, if no such score is available, the invention assigns the lowest possible value, namely 200. The Equifax scoring scores vary from 200 to 1000. The dummy variables in the above equation are defined as follows:

$$C0 = \begin{cases} 1 & \text{if the loan is current at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

$$D1 = \begin{cases} 1 & \text{if the loan is 1 month past due at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

$$D2 = \begin{cases} 1 & \text{if the loan is 2 months past due at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

$$NO\ SCORE = \begin{cases} 1 & \text{if the loan has no credit score available at the beginning of the time period;} \\ 0 & \text{otherwise.} \end{cases}$$

- 38 -

The coefficients A, B_1, B_2, B_3, B_4, B_5 and B_6 are estimated by running the model over the underlying portfolio.

All of the forecasting is done at the individual loan level and then the results are aggregated into the portfolio of interest by defining or grouping certain loan characteristics (location, rate type, maturity, LTV, etc.) to make comparisons. Even though the invention presents the mean probability for a predicted group, the information contained in the individual loan level data is preserved because the invention explicitly considers the dispersion around the mean of the bad rate over time.

To forecast the probability of an individual loan entering 90+ day default during the predetermined time period (i.e. the two year time frame), all one need do is insert the estimated coefficients and the characteristics of that individual loan into the logistic equation for "P" presented earlier.

The logistic model in the form of the aforementioned equation provides numerical results which are suitable of being graphically presented as shown in Fig. 5. The graph enables management to readily interpret and form decisions based on the predictions which it contains. In accordance with a further embodiment of the invention, the results are feedback by

- 39 -

the computer which then provides yes/no decisions based
on predetermined default risk or profit criteria set by
the operator.

5   Fig. 5 is a snapshot taken in 1996 and depicts
loan experience looking both backwards to the past two
years and forwards over a similar two year time span.
The vertical solid bars 72 represent the current mean
(expost) bad rates for a particular group over the past
two years. In other words, these bars show the mean bad
10   rate percentages of a group of loans that originated in a
particular year. For example, the bar 72 for the loans
originated in 1989 shows a bad rate of about 12.5%. The
score for the 1991 loans is just about 8% whereas the bad
rate for 1996 is quite low (under 5%), reflecting the
15   fact that this vintage of loan has not yet matured
sufficiently.

The hatched vertical bars 74 represent the
forecasted mean bad rates (exante) for the same group of
loans over the next two years. The value for the 1996
20   vintage is somewhere around 7% indicating an expected
delinquency rate of 7% even though the past two-year
performance had an actual bad rate of only about 2.5%.
The curve 76 represents the expected bad rate curve that
is obtained by modifying the forecasted bad rates by the

- 40 -

risk ratio on nearby vintages, and this shall be
explained more fully later on.

One should not place much emphasis on whether
the curve 76 is above the solid bars 72, since this may
5   merely reflect the normal pattern of seasoning for
mortgages. Nor should one place much emphasis on the
absolute height of each bar, since this may reflect
different expectations among the various groups or types
of loans that are being analyzed. Instead, the graph of
10   Fig. 5 indicates three important benchmarks for reviewing
and forecasting the risk in the given loan portfolio.
First, note the jump which is indicated by the arrow 84.
It represents a jump which occurs when the difference
between the hatched bars 74 and the solid bars 72 is
15   greater than one standard deviation above the historical
age weighed performance for that vintage. The bigger the
jump, the more serious the quality problem. This measure
is particularly useful on younger vintages, e.g. the 1996
vintage to which the arrow 84 is pointed.

20   Second, the size of the portion of the hatched
bars 74 which protrudes above the expected bad curve 76
indicates an unusual level of risk in the past or the
future for that group of loans. Note the arrows 80 and
82 which indicates such conditions. Finally, the arrow
25   78 indicates a turning point which represents the point

- 41 -

at which the first derivative of the expected BAD rate
curve changes sign from positive to negative: i.e. the
first time the bad rate drops as the loans age increases.
The younger the age at which the turning point occurs,
5   the earlier the portfolio's credit performance will or
has matured.

      The manner in which the curve 76 of Fig. 5 is
derived may be better understood by reviewing Figs. 6 and
7. More specifically, the curve 86 is developed by
10   taking a snapshot at a point in time looking at loans of
different quarterly ages and asking how many in each age
group entered the "bad" state during the preceding
predetermined time period, e.g. two years.

      Initially, the EWS 34 develops for each
15   empirical two-year period of performance the bad rate
curve as a function of age in quarters. See the
quarterly bad rate curve 86 in Fig. 6.

      Next, using a moving average, the invention
smooths each curve to reduce the randomness of the
20   quarterly performance, thus obtaining the smooth curve 88
in Fig. 6. In fact, the slopes of the yearly bad rate
curve are calculated as the percentage change in bad
rates from one year to another year, which is known as
the risk ratio. To improve the integrity of the results
25   and protect against possible statistical aberrations, at

- 42 -

least eight two-year time periods are considered, with
the means and standard deviations of the risk ratios
calculated.

To find the point on line 76 for 1991, the
invention uses the point on line 76 for 1990 which has
the expected bad rate for 1990. Multiplying this bad
rate by the corresponding mean risk ratio from Fig. 6
obtains the expected bad rate for 1991 and its standard
deviation. This expected bad rate is used for the point
on line 76 for 1991. However, if the forecast bad rate
(bar 74) is within the expected bad rate, plus or minus
one standard deviation, the invention just substitutes
the expected bad rate by the forecast bad rate so that
the line 76 passes through the top of bar 74.

The third in the triad of dynamic underwriting
tools of the present inventions, the matrix link system
36, uses the information developed by the Crus Classes
technique 34 and early warning system 32 to develop a
probability based prediction of how many of a given set
of loans will be "bad" at a selected future date.

More specifically, while the Crus Classes
method 34 analyzes the past performance of loan vintages
and the EWS system places a probability on a group of
loans entering the bad state within a preset time frame,
i.e. a window, the matrix link system 36 is designed to

- 43 -

predict the default status performance of a group of

loans at a preset point in time within the window of

operation of the EWS. For example, the EWS method is

able to say with respect to a group of loans that 3% of

5   those loans will enter a bad state (90+ days in arrears)

at one time or another during a two year window. In

comparison, the matrix link is designed to answer the

question how many loans will be non-accruing, i.e. in the

90+ payment overdue state, at the end of the first

10   quarter of the two year window or nine months into the

window and so forth, taking into consideration that some

loans may enter the bad state or exit therefrom due to

prepayment or on account of having been matured, or by

completing foreclosure.

15   To perform its functions, the matrix link

system 36 predicts how many borrowers that enter a

90-days delinquency state remain there, how many loans

will return to "good" status and, finally, in which

quarter over the predefined window, e.g. two years, will

20   these transitions occur. Note that a particular loan can

enter a bad state, return to a good state or remain in a

bad state. Loans may mature, pay off or complete

foreclosure during the predefined window period and thus

exit the loan portfolio being analyzed. In order to

25   provide a quantitative measure of the transitions of

- 44 -

loans between different states, the present inventors
have developed a so-called delinquency transition matrix
in a form which, in one embodiment thereof, appears as in
the table in Fig. 7.

5   In the table of Fig. 7, use is made of a
historical file spanning four years and including vintage
years 1993-1996. The table shows the delinquency
performance of a particular group of loans. Further, the
table stratifies the loans by age of origination. Note

10   that the table lists separately the results for three
different types of loans, namely conforming loans, jumbo
loans and government loans. In each case, it shows the
probability of a loan transitioning (a) from a bad state
to a bad state, (b) from a bad state to a good state; (c)

15   exiting, i.e. maturing and therefore being dropped from
the sample of loans being considered, (d) from good to
bad, (e) from good to good; and (f) from good to exit
state.

           Using the percentages listed in the delinquency

20   transition matrix in the Table of Fig. 7, one can then
begin to convert the information obtained through the EWS
system 32 into the forecasts of how the Crus Classes
vintages will perform at predefined time periods within
the window. The table in Fig. 8 illustrates the formulae

25   evolved by the present inventors which are as follows.

- 45 -

First, the current age of the loan at the time
of forecast is determined. In the table of Fig. 7, the
age of the loans is indicated in years (1, 2, 3, 4...
10). However, in an actual implementation of the
5   invention, the vintages have been stated and the formula
is calculated in terms of quarters to obtain increased
accuracy.

For each group of loans of a particular age,
the invention uses a 3-month transition matrix to
10   forecast three months forward, a 6-month transition
matrix to forecast six months forward, a 9-month
transition matrix to forecast nine months forward and a
12-month transition matrix to forecast twelve months
forward.

15   Based on the choice of data in the previous
step, the invention calculates respectively looking
forward three, six, nine and twelve months:

1. how many good loans and bad loans will
exist from the portfolio;

20   2. how many good loans will turn into
bad; and

3. how many bad loans will remain bad.

From the above data, one obtains the classic
"roll-rate" forecast which provides the first component
25   of the forecast. The above approach merely projects

- 46 -

forward the results that have already occurred in the
past, on the expectation that they will repeat
themselves. However, a greater benefit of the matrix
link technique of the present invention comes from adding
5   the additional information that is contained in and/or
obtained by the early warning system 32.

          To this end, the invention:

          (a)   Calculates an empirical ratio
obtained as -- the cumulative number of loans which are
10   90+ at each quarter (EOP) and divides it by the number of
loans that are 90+ at least once during these four
quarters.

          (b)   From the EWS, the invention obtains
or forecasts the "bad" rate for the two-year window based
15   on the EWS method 32.

          (c)   Using the EWS, the invention
forecasts the bad rate and the empirical ratio above as a
new piece of information to adjust the classic "roll-
rate" forecast. This is in essence what comprises the
20   "matrix link" method 36. Fig. 9 provides the results of
the matrix link in graphical form. In the example shown,
the performance of different vintage loans is predicted
one year forward in quarterly installments starting in
1997.

- 47 -

For example, the plot 102 shows the two-year
performance of 1995 vintage loans which range in age
(months) from 0 to 24 months, as viewed looking backwards
in time in 1997. The curve 104 shows the delinquency
5   rate percentages predicted for the next twelve months.
For example, when the groups of loans attain an age of
27, the delinquency rate can be read on the ordinate
axis. The same is true for this group of loans when they
reach an age of 30 months, 33 months and 36 months. The
10   reason that the curve 104 has a predicted value below the
actual value is that the prediction in the matrix link
uses a moving sum average which weighs down the actual
sharp up-turn in the "bad" rate which has actually
occurred toward the end of the curve 102.

15   The above remarks are also applicable to the
curves 106, 108 which apply to the 1993 vintage, the
curves 110 and 112 which are applicable to 1994 vintage,
and to the curves 114 and 116 which apply to the 1996
vintage.

20   Note that the Crus Classes are less static than
traditional mortgage vintage analysis. Therefore, the
performance of the last three points of any vintage can
still change somewhat, for better or worse.

The matrix link lines, i.e. the curve 104, 108,
25   112, and 116 also show where the inventors expect the

- 48 -

last three Crus Classes points to adjust over the next
nine months.

The system of the present invention lends
itself easily to being implemented through use of a
5   general purpose programmable computer as illustrated in
Fig. 10. Thus, the general purpose computer 124
communicates with a local database 122 which receives a
wealth of statistical and specific information about
various loans from diverse sources. For example, the
10   source of the information may be a national loan database
120 which is maintained by certain industry groups. The
general purpose computer 124 has the usual complement of
peripherals including an operator's console 126, ROM 128,
RAM 130 and a hard disk 132.

15   The computer 124 operates under control of
major software blocks which perform the dynamic analysis
134 in a manner already described. The main software
components are the software routines 136 which handle the
development and analysis of the Crus Classes associated
20   with the creation of the loan vintages. The early
warning system block 138 calculates probabilities of
loans going bad within a predetermined forward looking
window. Finally, the matrix link software block 140
forecasts the probabilities that a fraction of loans will
25   go bad within the window at a particular time.

- 49 -

The analytical results developed by these
software subroutines or blocks 136, 138 and 140 are
tabulated in the tabulation software block 150 and
outputted through an output software block 152. The
5   output can be in the form of a signal which drives a
printer which generates a graphical representation of the
results in the manner previously described.
Alternatively, the output may supply the results to the
console 126 for visual inspection by the operator.
10   Alternatively, the operator may program the computer 124
via the console 126 to provide yes/no answers as to
whether an investment should be made or continued to be
made in a particular loan portfolio, again as already
described.

15   Although the present invention has been
described in relation to particular embodiments thereof,
many other variations and modifications and other uses
will become apparent to those skilled in the art. It is
preferred, therefore, that the present invention be
20   limited not by the specific disclosure herein, but only
by the appended claims.

WHAT IS CLAIMED IS:

1.   A process for analyzing and selecting loan
portfolios, wherein each loan portfolio comprises a
plurality of loan units, the process including the steps
of:

5   separating the loan portfolios into a plurality
of loan vintages in a manner such that the loans included
in each loan vintage have origination dates that are on
average of the same age and said origination dates of
each loan portfolio are all within a first time interval
10   and the respective time periods of the different loan
vintages being mutually exclusive of one another;

counting a bad rate of the loans in each loan
vintage by counting the loans in each loan vintage on
which payments are in arrears for a time period greater
15   than a second time interval during a time window having a
third time interval, wherein the third time interval is
substantially greater than said second time interval; and

providing a comparison of the bad rates of the
different loan vintages on a visually perceivable output
20   medium, to allow comparing the bad rates of the different
loan vintages.